Forecasting

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Acknowledgement

Forecasting: Principles and Practice

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- New open standards created in the mobile era, such as HTML5, will win on mobile devices (and PCs too). Perhaps Adobe should focus more on creating great HTML5 tools for the future, and less on criticizing Apple for leaving the past behind. (Steve Jobs about Flash in 2010)

Applications

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- Stocking an inventory based on forecast of stock requirements

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- how well we understand the factors that contribute to it;
- how much data is available;
- whether the forecasts can affect the thing we are trying to forecast.

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- the fact that we can forecast electricity demand does not seem to affect the forecast

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- there is a lot of past data available
- the fact that we can forecast stock prices will lead to change in market dynamics and it will affect the forecast

Example of Forecasting

Forecast of production of beer in Australia

Dark blue lines show the mean forecast
Light blue band shows the confidence interval

Three Types of Forecasting Models

Task: Forecast Electricity Demand at Time T

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3. Mixed model
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- There are some large dips in load around the start of each year. These are due to holiday effects.

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- **Cyclic**: A cycle occurs when the data exhibit rises and falls that are not of a fixed frequency.

Seasonal v/s Cyclic

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- Seasonality: within every year, there is pattern of sales
- Cyclic: Every 6 years or so, there is a similar pattern

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Thus, very difficult to forecast

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  - Let us assume we are forecasting monthly and we want to forecast for Mar 2020 (month=3) and current time is Jan 2020 (month=1). Thus, $h = 2$. Let us assume yearly seasonality, i.e. $m = 12$. Thus, prediction for Mar 2020 is value at (Jan+2 months) - $12 \times 2 - 1\%12 =$Mar 2020 - 12 Months = Mar 2019

Simple Forecasting Methods

Learning: Simple solutions often work well, especially if you know about the domain.

Evaluating Forecast Accuracy

Timeseries cross-validation for 1 timestep ahead prediction

Question: How do you nested CV?

Answer: Similarly divide the train into train and validation preserving the notion of timeseries.

Evaluating Forecast Accuracy

Timeseries cross-validation for $k = 4$ timestep ahead prediction

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- White noise series is stationary — it does not matter when you observe it, it should look much the same at any point in time.

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- Series with seasonality: d, h, i
- Stationary: b and g (cycles are aperiodic)

Differencing

What is the relation between a and b?
b is the first order time difference of a!
b is stationary, while a is not!

Differencing

For (a) the ACF is significant
For (b), the ACF declines rapidly

Autoregression

$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$,where ε_t is white noise.